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A Novel Approach to Evolutionary Robotics

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1 Introduction

Evolutionary computing draws inspiration from the natural process of evolution to develop algorithms for optimisation and design. The field has developed a range of widely applicable metaheuristics that exploit the principles of evolution in software. Evolutionary robotics is a sub-field of evolutionary computing that uses the principles of evolution to design robot controllers and/or hardware, often using computer simulations to evaluate candidate solutions. Evolution typically takes place *off-line*: the robots are deployed after evolution has terminated with an acceptable result, and no further adaptation takes place. Over recent years, interest in *on-line* evolution has increased [3].

The field is about to enter a new phase with the development of algorithms where evolution takes place at the hardware level, in particular to allow ecosystems of evolving autonomous machines that can adapt to their environment. A framework for such an ecosystem in which physical robots actually reproduce was proposed as the Triangle of Life (ToL) [5]. This abstract presents the first ever implementation in hardware of an important part of that triangle, namely the autonomous mating of physical robots and conception of their offspring.

The ToL framework combines two novel aspects. The first is that it captures a life cycle that does not run from birth to death, but from conception to conception, explicitly making robot birth part of the evolutionary process. Secondly, it envisions on-line evolution of both robot morphology and control in hardware, as the robots operate in their task environment. New robots are created continuously (triggered by robots meeting and autonomously deciding to mate) and is limited only by the availability of building blocks and the capacity of a 'birth clinic' where new robots are automatically constructed. This defines an ecosystem of continuous evolution and adaptation [5].

There have been proof-of-concept ToL implementations in simulation (e.g., [6]) that were in principle transferable to hardware, but the actual step to a hardware implementation has not yet been made. Components of a full ToL implementation in hardware do exist, e.g., the automatic assembly of evolved robots [2]. These, however, lack the aspect of autonomous mating with local mate selection (i.e., they have a centralised control loop that controls evolution) and of lifetime learning to adapt control to the new morphology.

The experiments described here consider exactly these aspects and so provide an essential missing piece for a real-life ToL implementation.

2 Experiment

These exeperiments address two parts of the ToL life cycle: lifetime learning, where the robots optimise their controller to suit their body plan, and evolution of morphology, where robots autonomously exchange genotypes –schematics of theirs body structure– to combine into a new individual.

Figure 1: First hardware implementation of Triangle of Life.

Our implementation encodes the robot morphology in a genotype specified in the RoboGen framework. This was designed specifically to allow robots to be easily manufactured through desktop 3D-printers and the use of simple, open-source, low-cost electronic components [1]. RoboGen uses a tree-based representation where each node represents one building block of the robot. It contains information about other blocks that it is attached to, its type, name, orientation and, in our

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version, its colour. The colour parameter is added to allow easily tracking which body parts stem from which parent. We use the open source RoboGen library for crossover with a slight modification to support colour information.

The robots employ the RL PoWER reinforcement learning algorithm that enables arbitrarily shaped modular robots rapidly to develop a suitable gait. Robot controllers consist of a set of spline functions, the control points of which are adapted through an actor-critic model to maximise locomotive performance. The applicability of this method for robot locomotion was investigated in [4].

Two robots with predefined shapes are placed in a small arena as shown in Fig. 1. Because their controllers are randomly initialised, their first task is to learn effective locomotive behaviour. The robots are equipped with a photocell that allows them to detect a light source placed at the edge of the arena. The robots can gauge the efficacy of their controllers by monitoring the intensity of the light source. If the robots succeed in learning to locomote, they will reach the light source. Once they are close enough (again indicated by light intensity), they are deemed ‘fit’ and ‘mature’ enough to procreate and start communicating to exchange genetic material.

The robots transmit their genome to a server that recombines two received genomes into a new inddividual (note that the server is only a channel of communication, it does not constitute a central overseer of the evolutionary process).

The component parts of that new individual can then be printed and assembled and the resulting robot can be placed into the arena, closing the loop and allowing for evolution to adapt the robot population to the environment.

Fig. 2 shows the body plan that results from the first successful recombination of the two parent robots from Fig. 1. The offspring robot is yet to be assembled and placed in the arena, but it is the first ever offspring of two real robots mating autonomously. This constitutes a major milestone on the road towards an ecosystem of autonomously evolving robots. The next hurdle on this road is the lack of automatic assembly, a problem that remains yet to be solved.

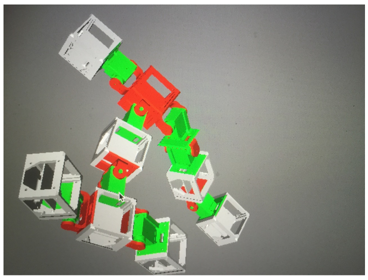

Figure 2: A representation of first successful genotype crossover between two hardware implemented robots.

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